A Comparisons of Model Based and Image Based Surface Parameters Estimation from Polarimetric SAR

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Abstrat:-Surface can be characterized in terms of its material (dielectric) and geometric properties. The dielectric properties of the surface are expressed primarily by its moisture content, while the roughness describes the geometric characteristics of surface. Various techniques for information retrieval from remotely sensed data have been proposed in a number of recent studies. Some of them are based on an empirical relationship between the measured return signals and the ground truth. Because of their development from a limited number of observations, these models are generally valid only for the conditions under which those measured data were taken. These models also appear that no dependence on the roughness parameter, l - correlation length. In this work, the potential of using the polarimetric SAR data over surface scatterers in order to invert surface parameters is investigated. The model-based and image-based inversion schemes are investigated and compared; the former is doing retrieval from a dynamic learning neural network[1] trained with the **A**dvanced **I**ntegral **E**quation **M**odel[2-4], while the later is schemed from a decomposition of coherency matrix[5]. In model based approach, only the surface scattering term of total return is used in order to remove the vegetation effects. The image based approach accounts for nonzero cross-polarzed, backscattering as well as depolarization by three polarimetric parameters, namely the scattering entropy(H), the scattering anisotropy(A), and the alpha angle(α).The features of these two schemes are discussed in terms of numerical aspects and physical implications of the surface parameters being inverted by using experimental E-SAR L-band data . We also show the performances of inversion and discuss the advantages and drawbacks of both schemes.

I. Introduction

Much effort has been devoted to improving the accuracy of the IEM originally reported by Fung et al. [8]. This is mostly done by re-deriving the expression without or reducing the assumptions in the original development. One significant step made forward was the introduction of a transition function in the calculation of Fresnel reflection coefficients to take spatial dependences into account and thus remove the restrictions on the limits of surface roughness permittivity. Although the approach is kind of heuristic, it proves to perfectly work for a broad range of surface conditions. A heuristic approach is necessary since there are no analytic forms existing for an IEM version, called Advanced IEM (AIEM) [1,2], which contains many more terms compared to the original version, but remains in algebraic form for the ease of numerical implementation. In this paper, we apply the inversion scheme based on the dynamical learning neural network and the AIEM model to reconstruct the physical properties of soil surface from polarimetric SAR data. Parameters to be inverted include surface roughness in horizontal and vertical scale and dielectric constant which in turn is related to other interested geophysical quantities such as moisture content of soil. The co-polarized radar backscattering coefficients, as knows as sigma nought are defined as the average radar cross

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section per unit ground area in dB. They are used as the inputs of the inversion scheme.

II. Inversion by Neural Network Trained with the AIEM (model-based)

In order to avoid the drawback of slow learning process, we use dynamic learning neural network (DLNN) in which the necessary training time has been significantly reduced and the accuracy of process is as high as desired. Its effectiveness and usefulness have been demonstrated from a wide range of parameters acquired by various applications [6,7]. The training of DLNN beings with defining the network inputs and outputs that are determined depending on applications. For inversion problem as in this work, the outputs of the network are normalized roughness parameters, kL, $k\sigma$ and medium permittivity, ε. It should be focused at this point that the determination of the parameter bounds and proper selection of the training data are quite significant for DLNN training. The data sets should be sufficiently representative within the problem domain and provide ambiguous data as less as possible. In this study, the normalized surface correlation length "kL" ranges from 1.0 to 10.0 while the normalized surface roughness r.m.s. height "$k\sigma$" ranges from 0.1 to 1.0. And the real part value of dielectric constant ranges from 4.0 to 20.0 as the training dynamic range.

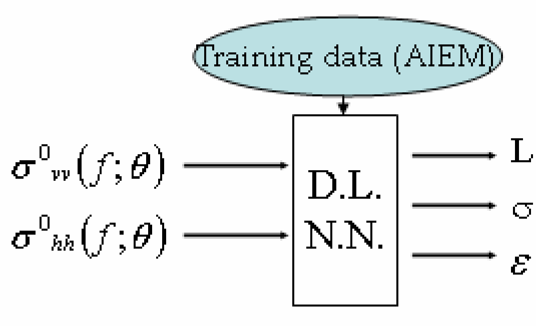

Figure 1. The inputs and outputs setup of DLNN

III. Inversion by Three Polarimetric Parameters of Coherency Matrix (Image-Based)

The image-based model (Hajnsek et al. 2003) [5] for the investigation of surface parameters from polarimetric SAR data is used to compare with the model-based one. The model is a two component model including Bragg term and a dielectric constant from the surface roughness, it is formulated in terms of the polarimetric entropy H, alpha angle α, and anisotropy A, which are derived from the eigenvalues and eigenvectors of the polarimetric coherency matrix.

Surface Roughness

The roughness parameters $k\sigma$ value are directly from their anisotropy values by using a linear approximation of the relationship as $k\sigma$=1-A. While the lower $k\sigma$ values are overestimated and higher underestimated, indicates that the use of a modified linear relation between A and $k\sigma$ may lead to even better inversion results. For small $k\sigma$ values, another regression can be used according to $k\sigma$=1.25-2A.

Soil Moisture Estimation

The computed entropy H and the alpha angle α values are used to estimate the dielectric constant. The estimation is performed by using a lookup table, which delivers the dielectric constant as a function of the entropy/alpha values and the local incidence angle. In this way, the range and topography induced variation of the local incidence angle across the image can be accounted for.

IV. Experimental Data Analysis

The well trained DLNN is applied to the measured data acquired at L-band (1.3 GHz) from E-SAR over the floodplain of River Elbe located in North-Eastern Germany [5] as shown in Figure 2. At L-band, the spatial resolution of the single look complex data is in azimuth about 0.75 m and in range about 1.5 m. The data were acquired in April and August of 1997 along two 15 km long and 3.2 km wide strips. Ground data has been collected in August 1997 over agriculture test fields with difference roughness conditions. Soil moisture measurements have been performed on five different locations at each test field. The fields are viewed with incidence angle (AOI) ranging from 48 to 50 degrees. The four fields were selected due to the vegetation covered and the choices of them were constrained by the image-based model (see Table I). To activate the DLNN inversion process, a total of 5000 training samples are generated using AIEM model within the range of parameters as mentioned above and three surface correlation functions, Gaussian, Exponential and 1.5 power. It shows that the varied inversion results using different correlated surfaces in AIEM model. All the retrieval results (mean value for each test area) are listed in Table II. First, we can see the deviation of roughness ($k\sigma$) between the inversion results and ground truth values. The largest deviation occurs for thje case of field A 5/16. Gaussian correlated surface matches best for the cases. It is interesting to note that 1.5 power correlated surfaces fall inbetween Gaussian and exponential correlated surfaces that represent two extremes of roughness spectra in terms of their bandwidth. For horizontal roughness scale, correlation length, there are no groud truth available, the comparison is excluded. Nevertheless, the inversion outputs are listed in Table II for reference. Next, we check the retrieved dielectric constants which may be related to moisture content. It is observed that the inversion results agree well with the ground truth. To indicate this point more clearly, we plot the inverted dielectric constants by model-based and image-based along with ground truth values (0-4 cm and 4-8 cm), as shown in Figure 3. The image-based results are out of bound, while the model-based results reasonably fall within the range of two different depths.

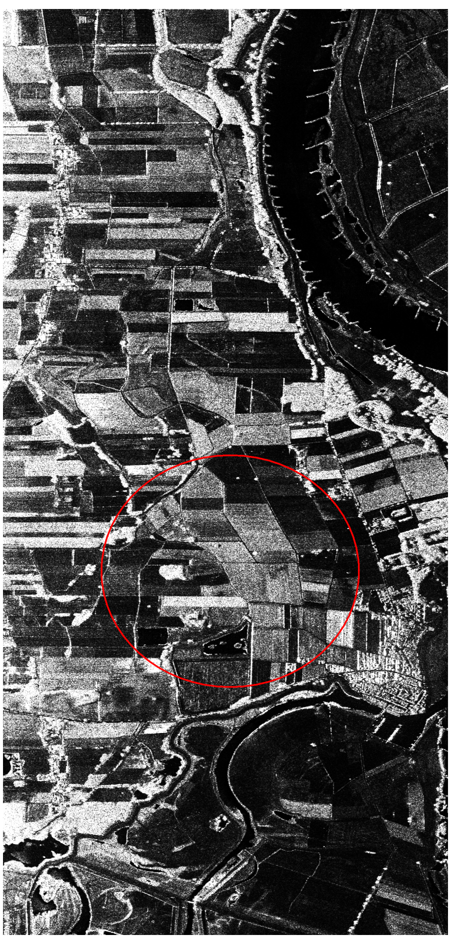

Figure2. Total power image of Elbe-Auen test area

Table I
Ground measurements for the Elbe-Auen test site.

Field ID	AOI	σ cm	$k\sigma$	ε' 0-4 cm	ε' 4-8cm
A 5/10	49.20	1.66	0.45	10.79	9.28
A 5/13	50.03	2.1	0.57	5.34	9.84
A 5/14	49.99	2.77	0.75	4.51	10.82
A 5/16	48.56	3.5	0.95	5.86	12.19

Table II
The inversion results of DLNN

A5/10	$k\sigma$	kL	ε'
Gaussian	0.51106	2.9856	8.8747
Exponential	0.36842	3.5310	10.552
1.5 Power	0.39530	3.0111	8.6624
A5/13			
Gaussian	0.61287	4.12425	7.6096
Exponential	0.30934	3.9752	5.5954
1.5 Power	0.36935	4.0491	7.8188
A5/14			
Gaussian	0.53227	3.7903	7.7906
Exponential	0.31289	4.0010	5.4194
1.5 Power	0.35864	4.1336	10.283
A5/16			
Gaussian	0.61799	3.6400	7.9737
Exponential	0.37857	3.8496	7.6764
1.5 Power	0.43115	3.7744	10.025

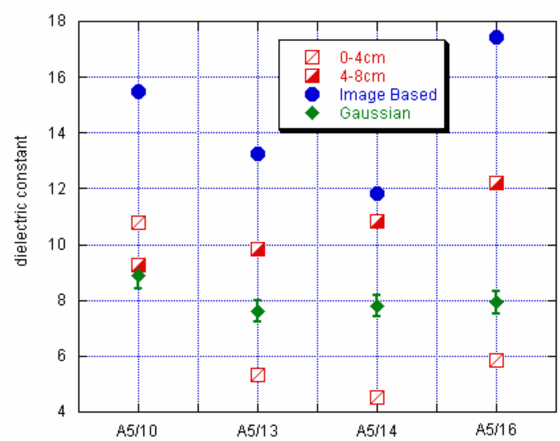

Figure3. Estimated versus measured dielectric constant for Elbe-Auen test sites

V. Conclusions

In this work, the inversion results of surface parameters estimation between imaged-base model and model-based with AIEM model are compared. The main advantage of the image-based model is that it allows a straightforward separation of roughness and dielectric constant estimation. It permits robust roughness estimates, widely independent on incidence angle variation. Although the inversion accuracy of image-based is high enough to point out the seasonal variation effect [4], the results of model-based perform

better obviously. Nevertheless, the main limitation for surface parameter estimation from polarimetric SAR data is the present of vegetation. It increases the entropy and decreases the anisotropy, leading to overestimation. The estimated value of $k\sigma$ using the "linear regression" [9] constrained by roughness parameter $k\sigma \leq 1$ is another problem which did not stand on physics. Moreover, the lacks of imaged-based, surface correlation length kL and imaginary part of dielectric constant, can not stand for the surface parameters completely.
The only drawback of the model-based is that the training data sets should be well representative with in the problem and the sensitivity of backscattering to surface roughness in like-polarized for the range of dielectric constant should be thought. Furthermore, the computed time depends on the number of input training samples. It takes less than one minute (over 5000 samples) in this study for each general correlated surface to AIEM model. Further determination of it should be carried out experimentally. An inversion model based on the DLNN was proposed in an effort to better estimation of soil surface parameter dielectric constant. Conclusion can be made that the proposed model can explain more closely the observed data and hence give the best inversion results.

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